Development and Application of a Global Benchmark on the Long-Term Climate Sensitivity of Soil Carbon Turnover

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Work presented here based primarily on:

Charles D. Koven, Gustaf Hugelius, David M. Lawrence, and William R. Wieder. "Higher climatological temperature sensitivity of soil carbon in cold than warm climates." *Nature Climate Change* (2017), doi:10.1038/nclimate3421

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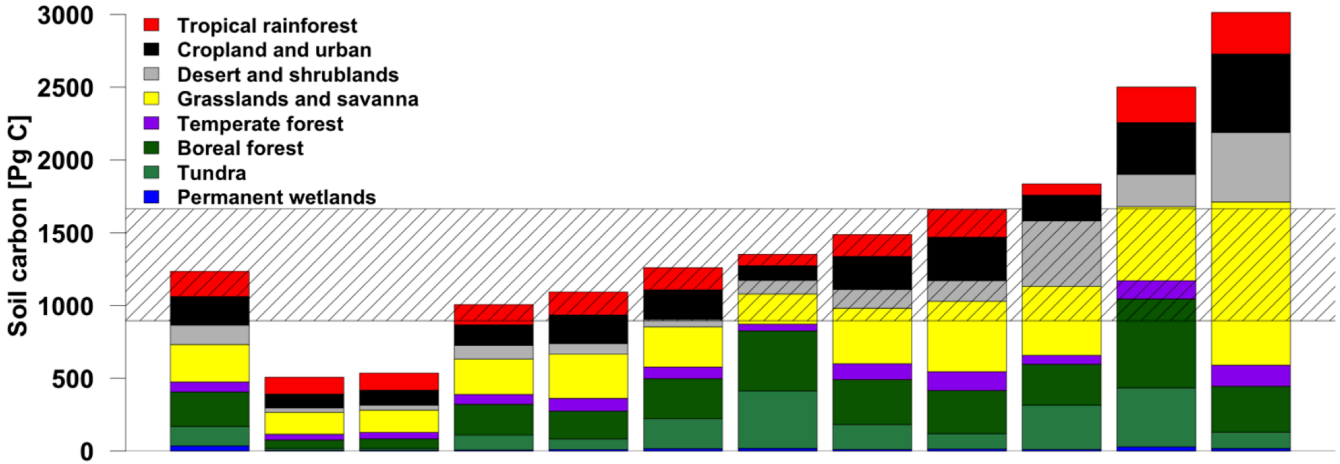
U.S. DEPARTMENT OF ENERGY | Office of Science

RUBISCO

Problem: ESM soil carbon models don't seem to have a lot of predictive power, even for the mean state. We'd like to benchmark to constrain models



Todd-Brown et al., 2013

Current ILAMB soil benchmarks

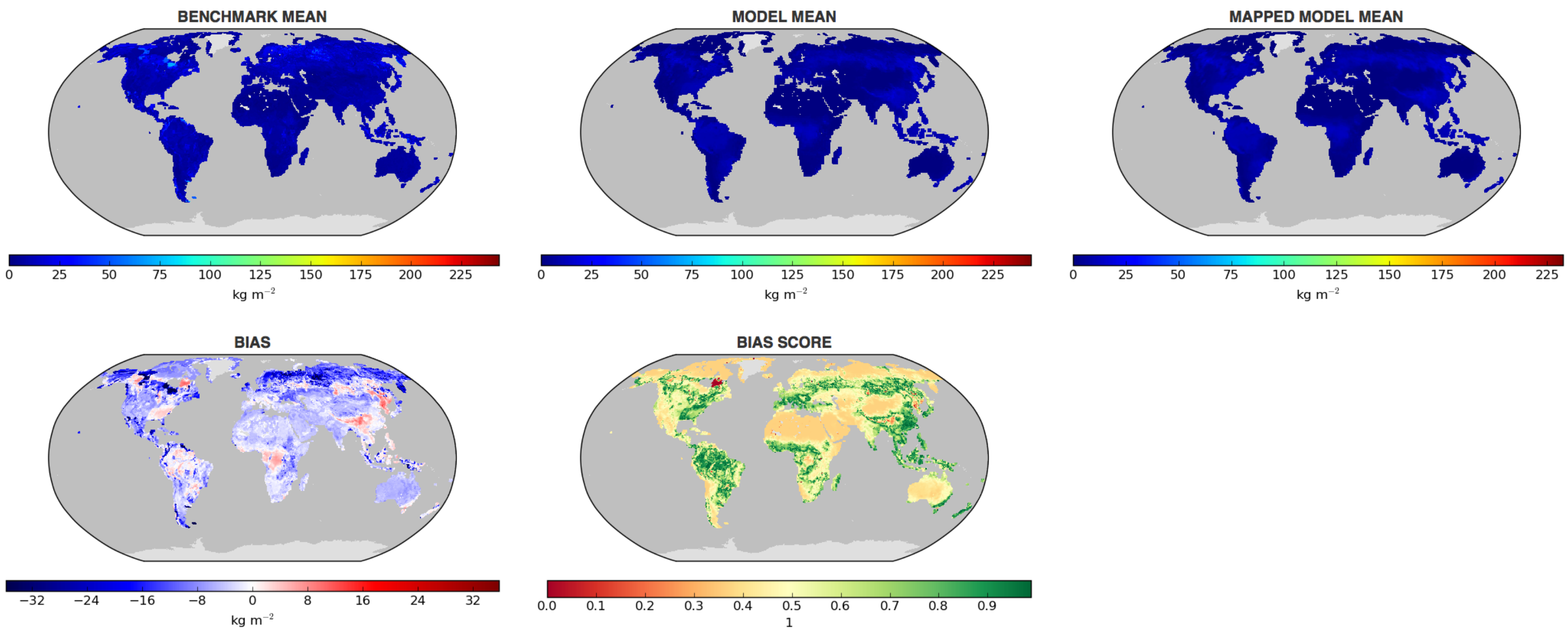
SoilCarbon / HWSD / 2000-2000 / global / CLM40CRUNCEP

Mean State | All Models | Data Information

Globe

Model	Data	Period Mean [Pg]	Bias [Pg]	Bias Score [1]	Spatial Distribution Score [1]	Overall Score [1]
Benchmark	[-]	1,295.165				
CLM40CRUNCEP	[-]	668.557	-640.496	0.583	0.618	0.6
CLM40GSWP3	[-]	498.855	-755.294	0.559	0.465	0.512
CLM45CRUNCEP	[-]	1,137.315	-65.471	0.604	0.586	0.595
CLM45GSWP3	[-]	857.208	-359.958	0.617	0.777	0.697
CLM50CRUNCEP	[-]	1,943.85	769.231	0.58	0.042	0.311
CLM50GSWP3	[-]	1,029.019	-186.057	0.6	0.178	0.389

Temporally integrated period mean



SPATIAL TAYLOR DIAGRAM

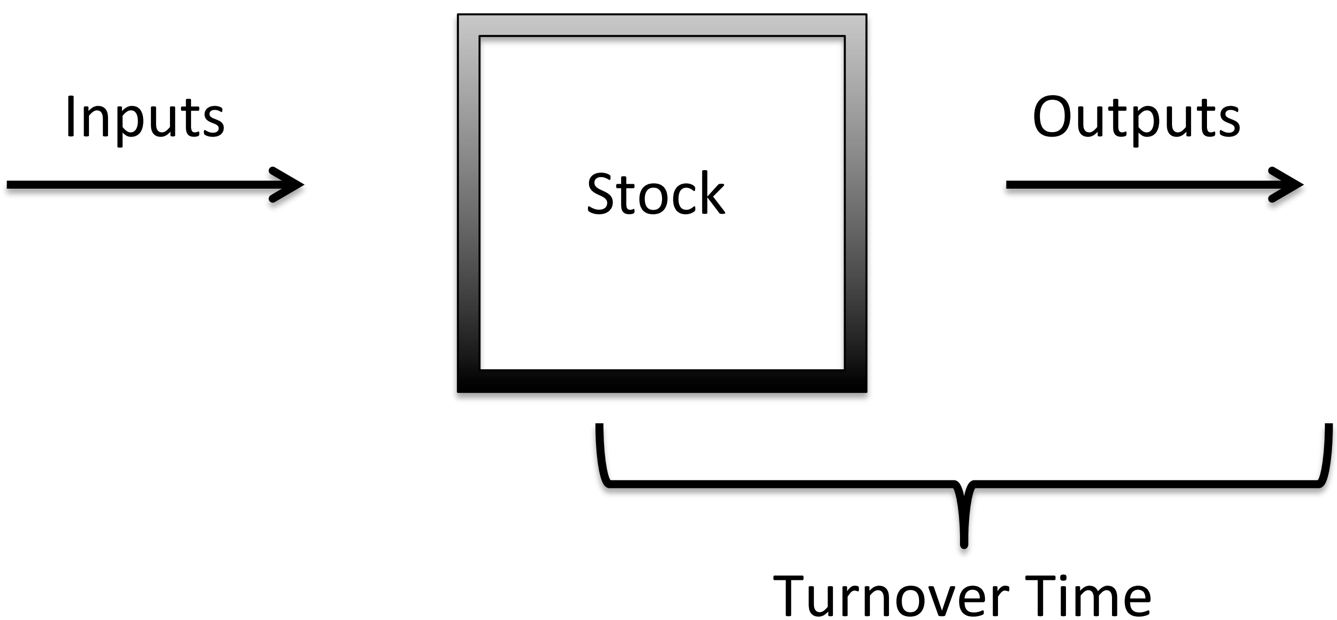
Some issues with current approaches

- Stock-based, so errors in plant inputs propagate into the soil and show up as errors in soil.
- Integral- or Spatially-based, so errors in climate show up as errors in soil.
- Large dynamic range of soil stocks means that errors in high latitude are weighted more than errors in tropics.
- Doesn't distinguish between what the models are trying but failing to predict (mineral soils) from things they aren't even trying to predict (peatlands).

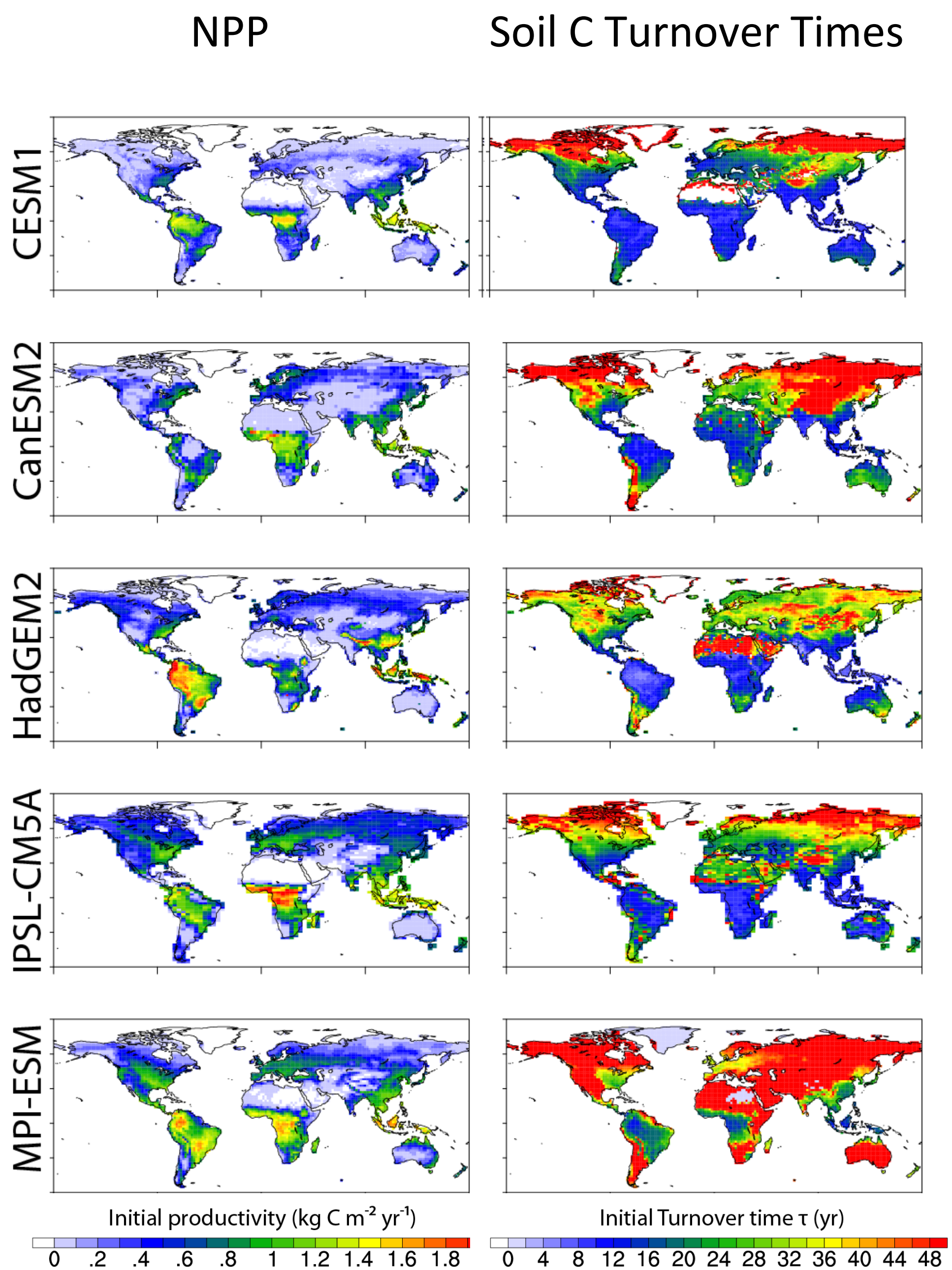
- Would like to construct some sort of relationship benchmark to mitigate some of these issues.

How to construct a simple model of soil carbon that works across the world's climates?

Simple reservoir theory: Treat soil system as a reservoir, in which losses are proportional to stocks

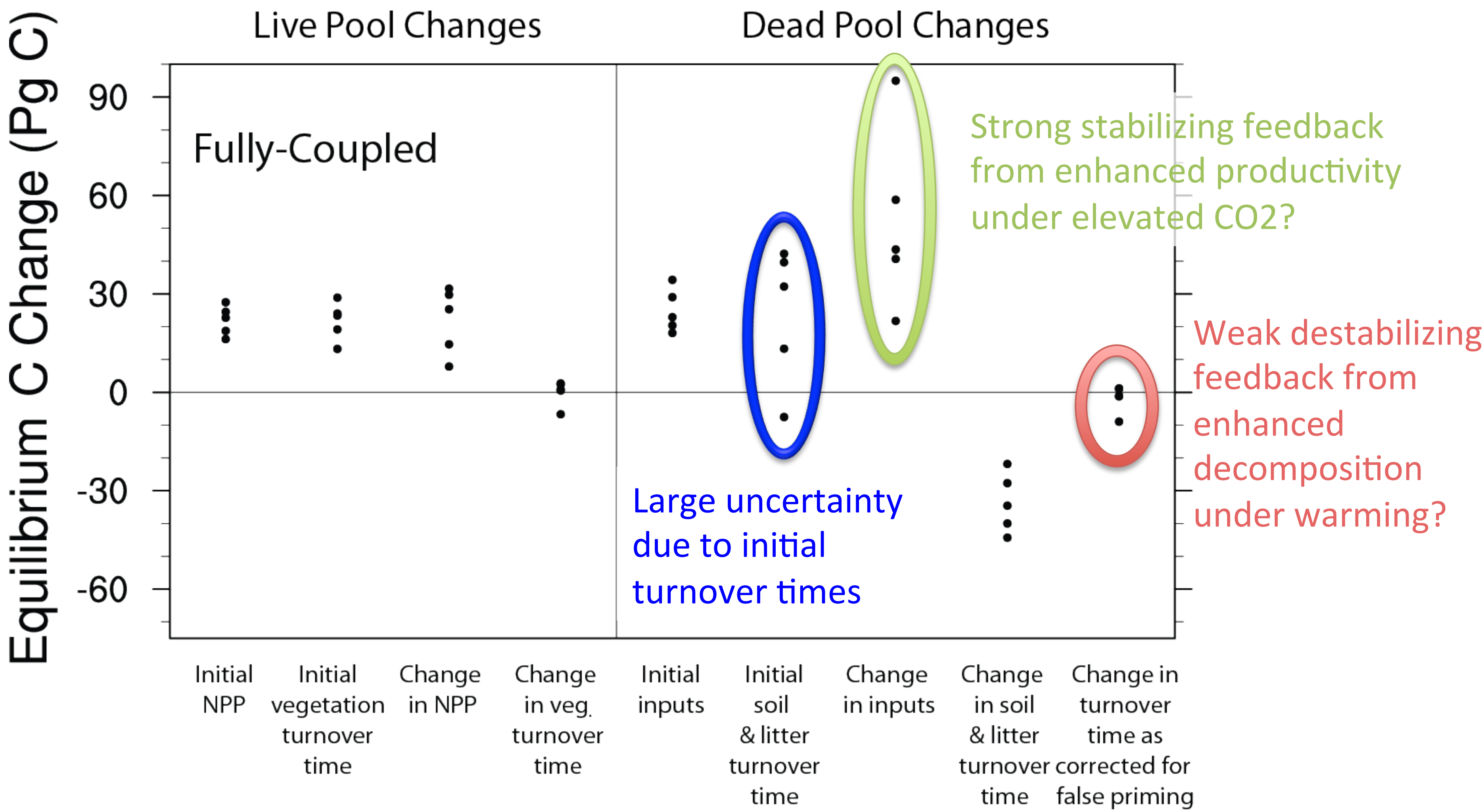


Initial Soil C stock uncertainty in ESMs dominated by turnover time uncertainty.



Koven et al., *Biogeosciences*, 2015

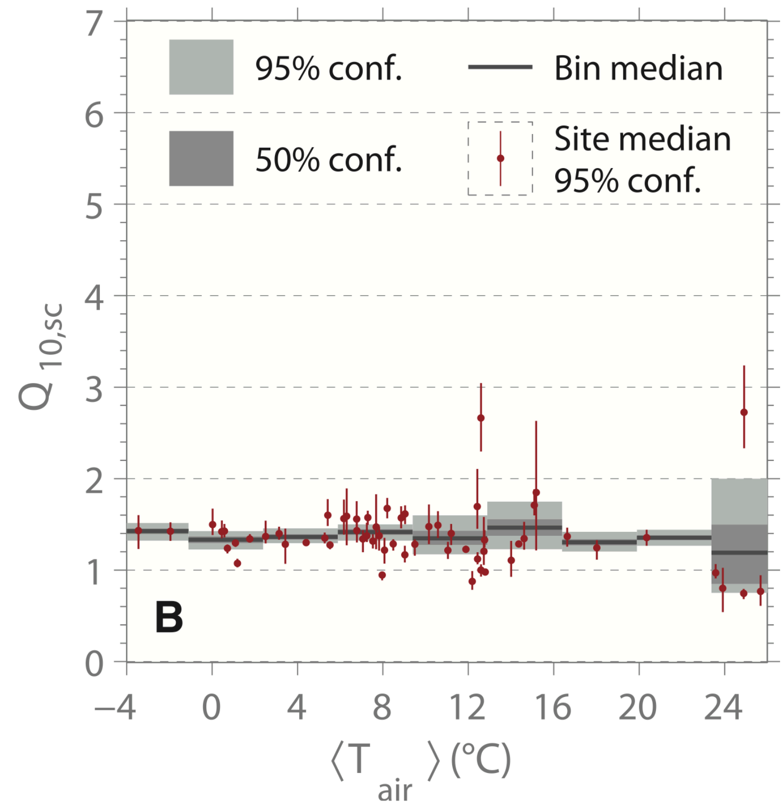
However, transient uncertainty in ESM carbon stocks mainly driven by productivity



Koven et al., *Biogeosciences*, 2015

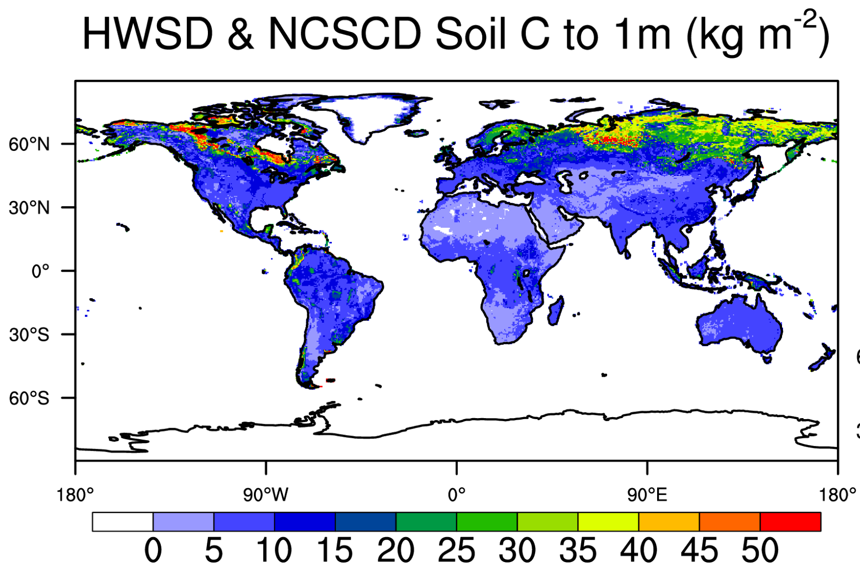
Temperature Sensitivity of respiration: the Q_{10} approximation

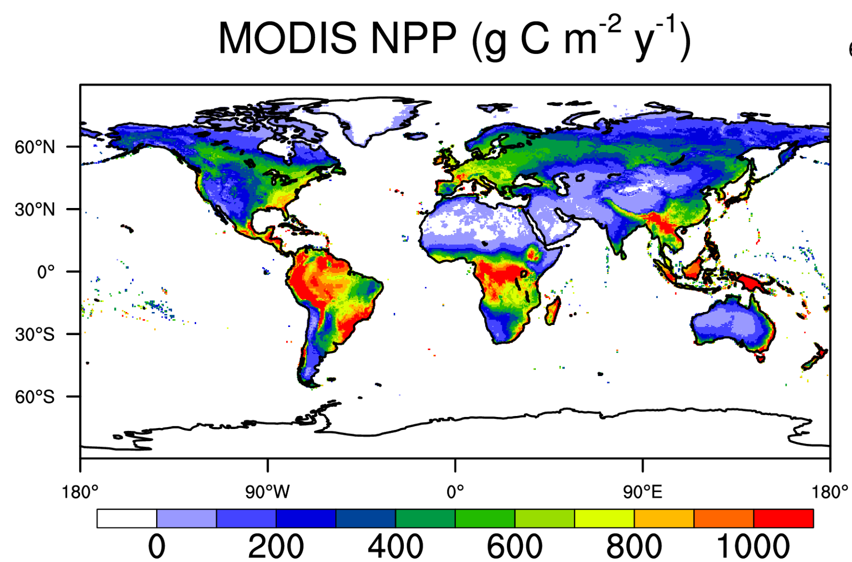
$$k(T) = k_{ref} * Q_{10}^{\left(\frac{T - T_{ref}}{10}\right)}$$

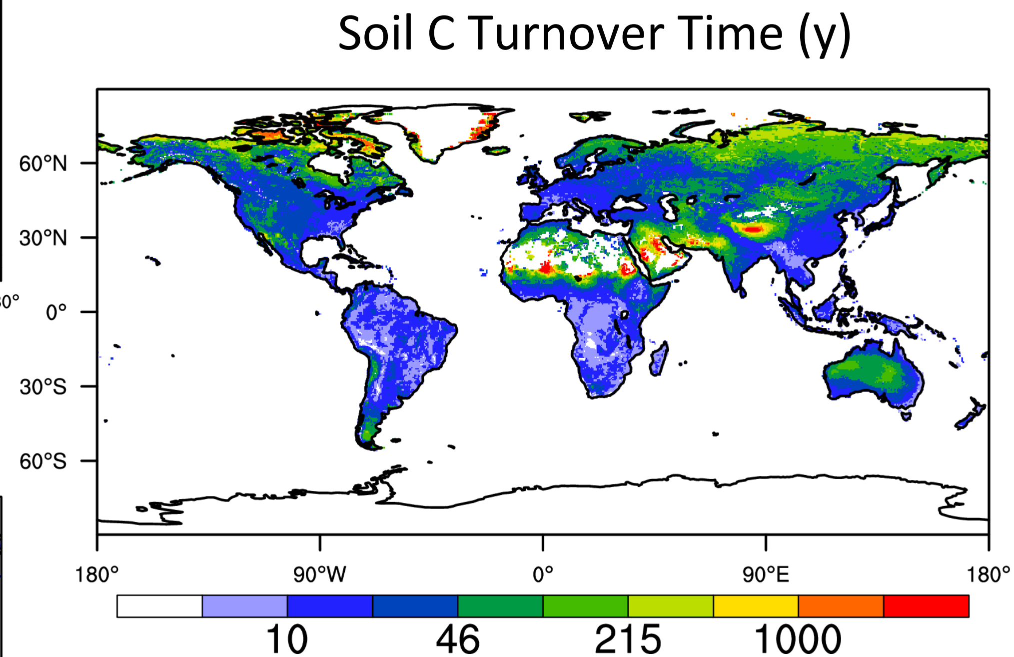


Mahecha et al., *Science,* 2010

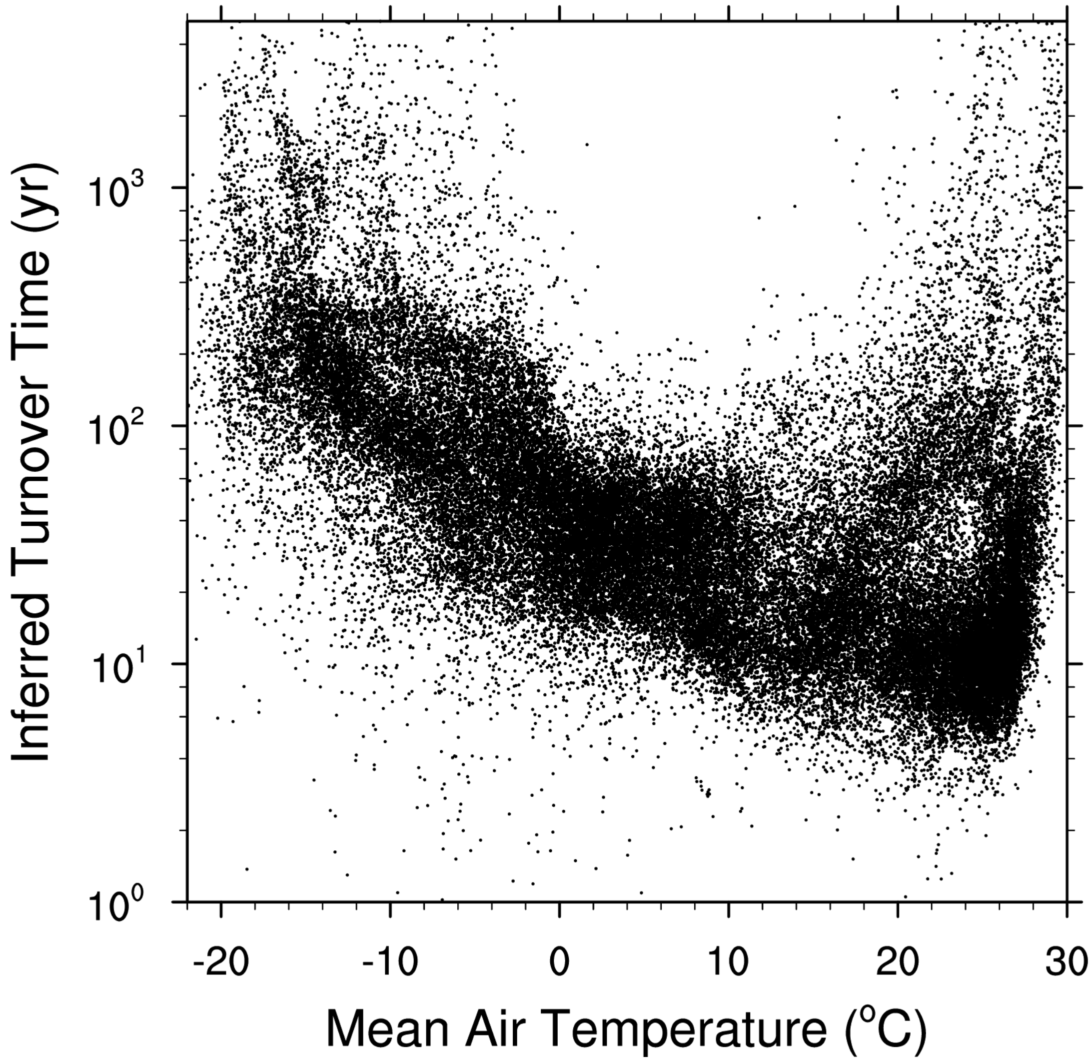
Calculate turnover time as ratio of carbon stocks to fluxes. Assumes quasi-equilibrium state.



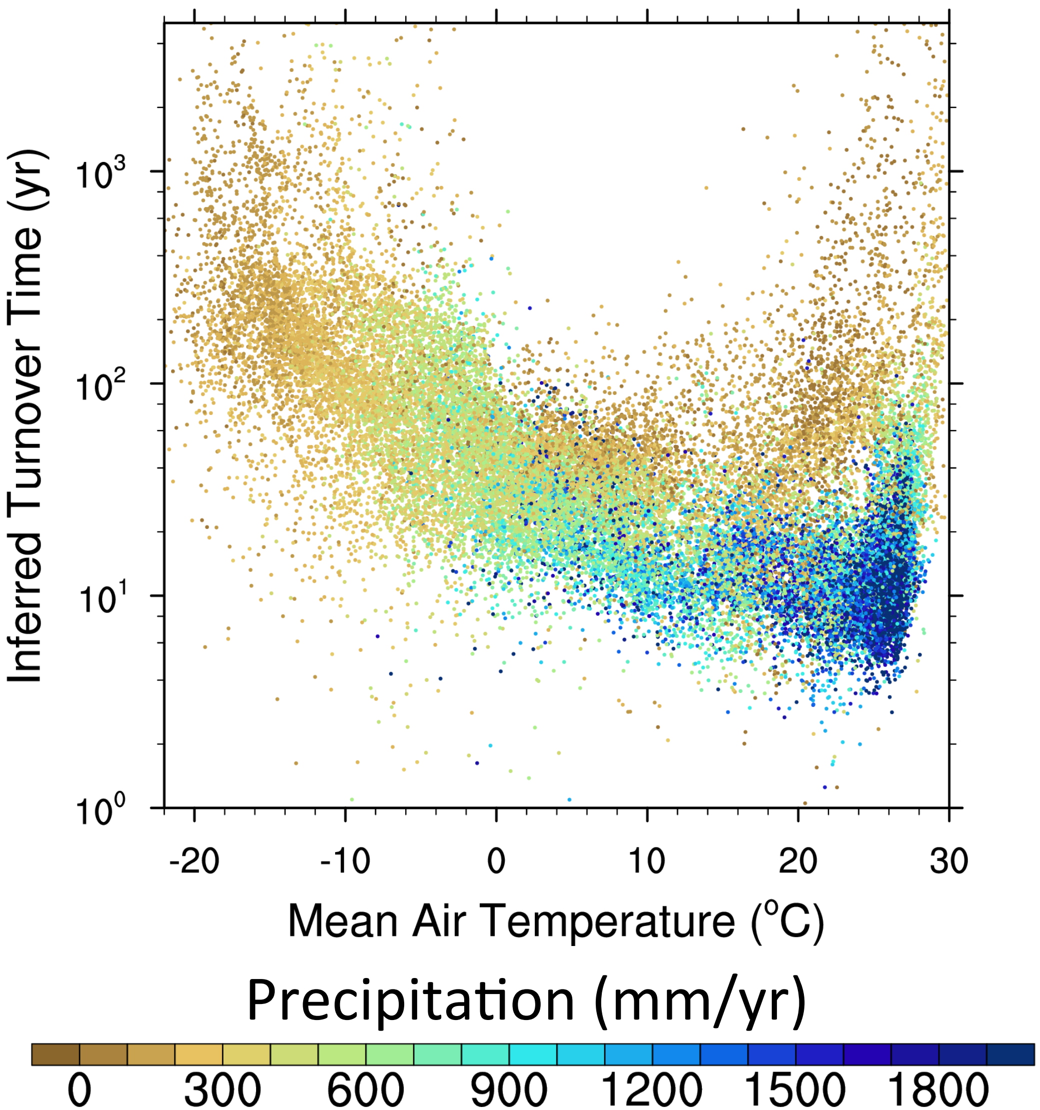




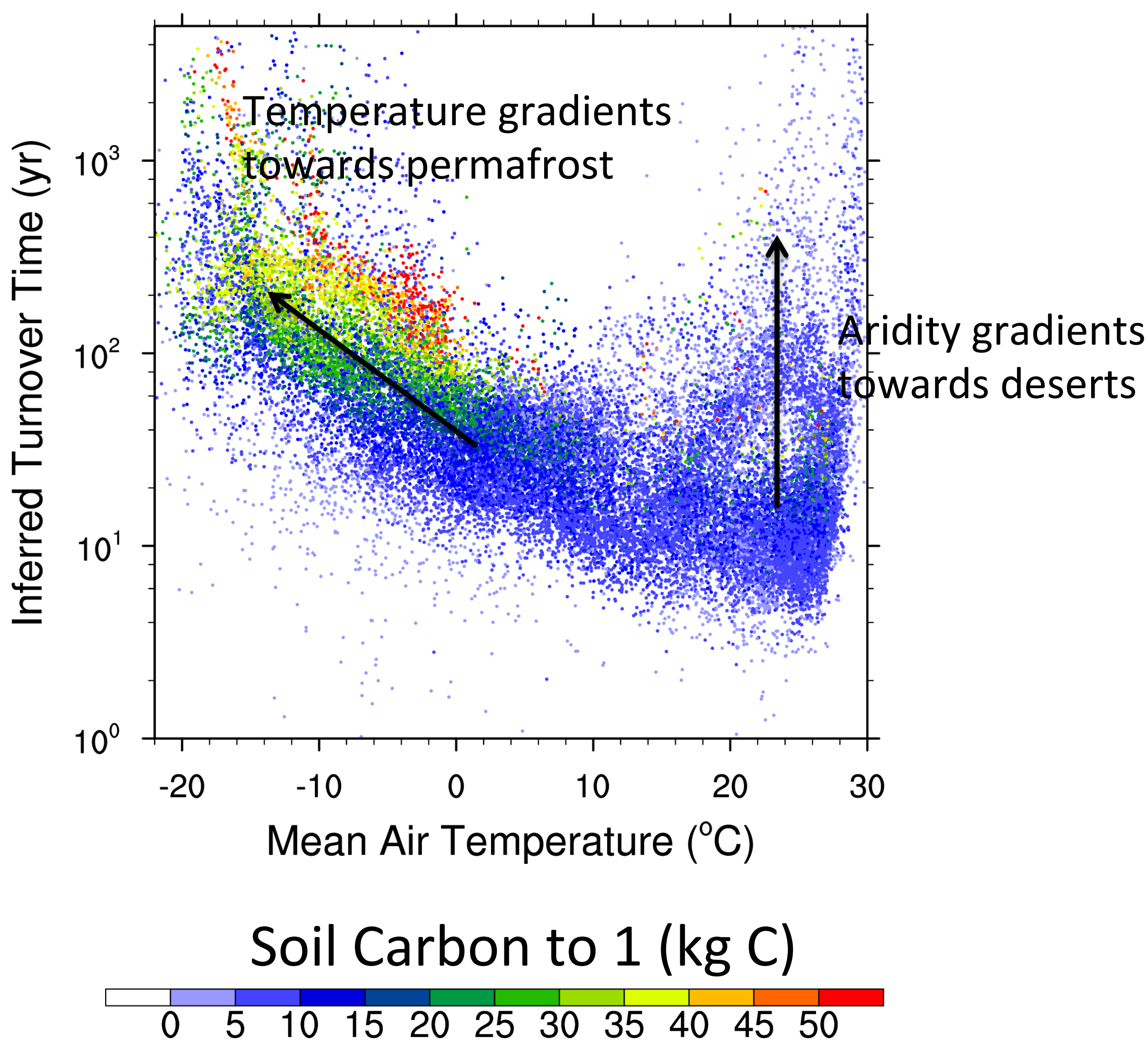
Plot turnover as function of mean annual air temperature



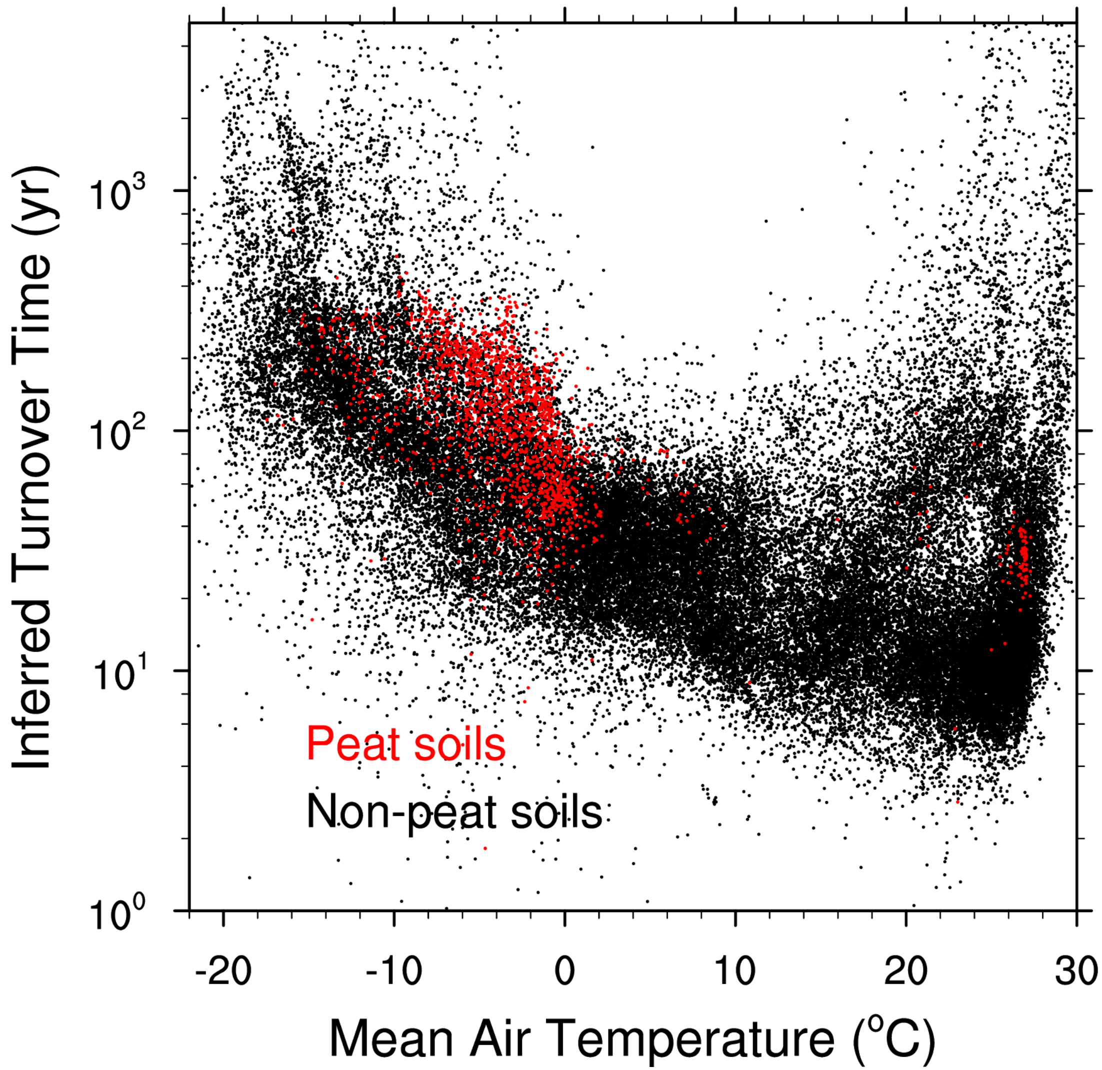
Color by precipitation to see where (low) moisture effects are dominant



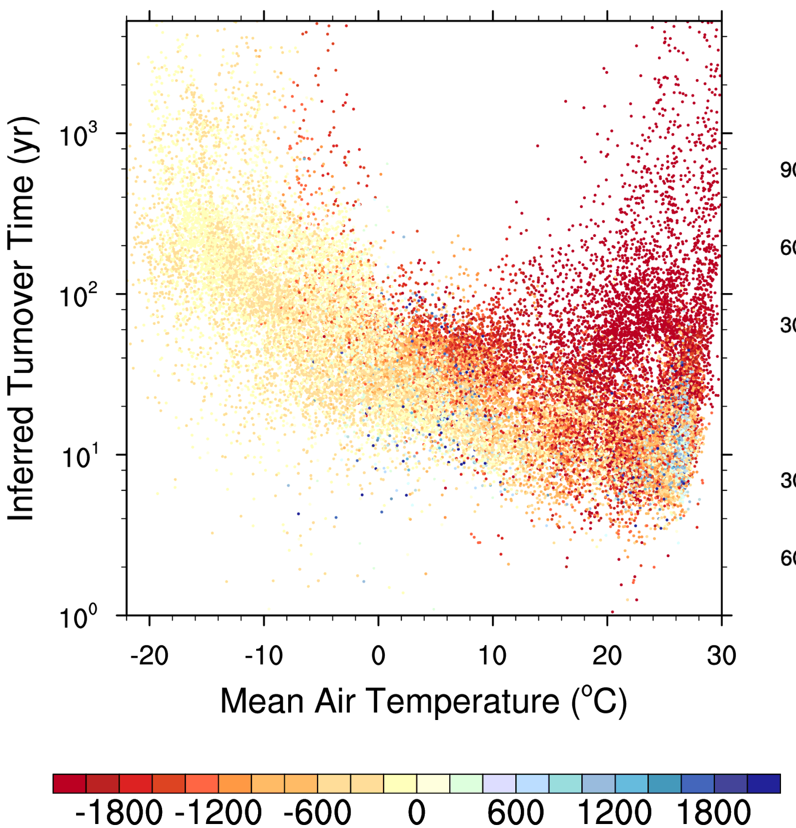
Limit condition of productivity becoming small and turnover becoming large along both aridity and temperature gradients, but high soil carbon only in cold climates

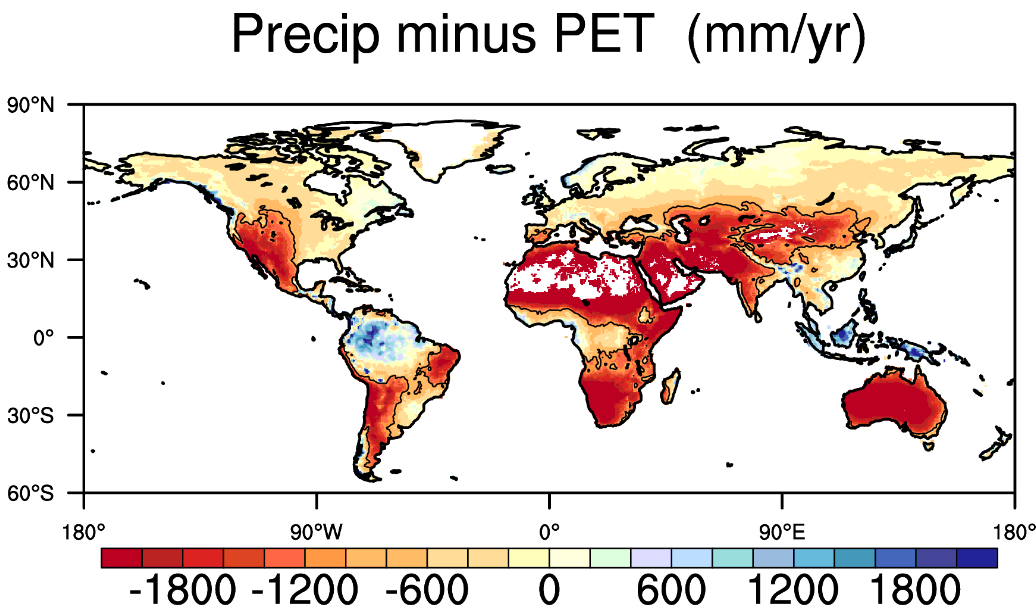


Identify peatlands to see where (high) moisture effects are dominant

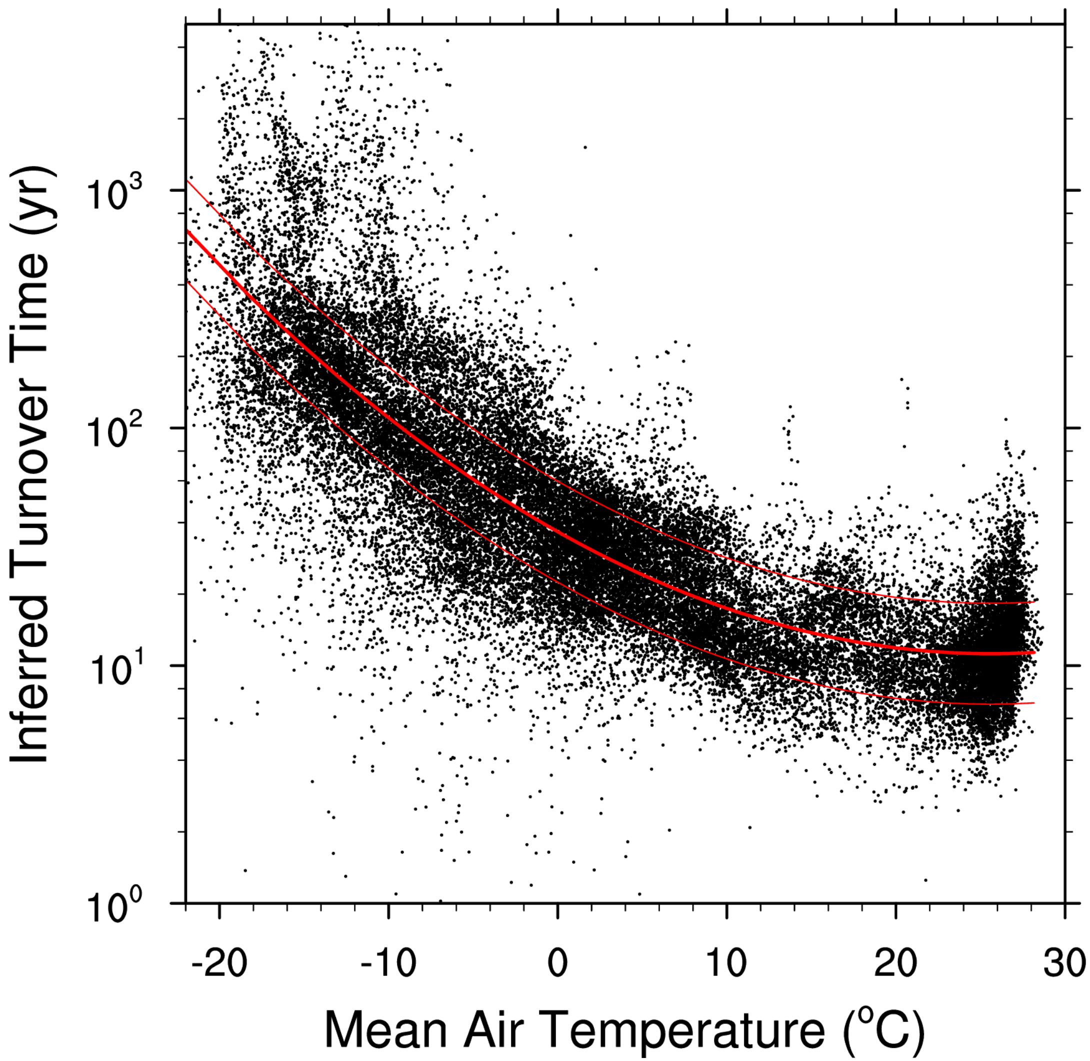


Identify (low)-moisture control by P-PET threshold

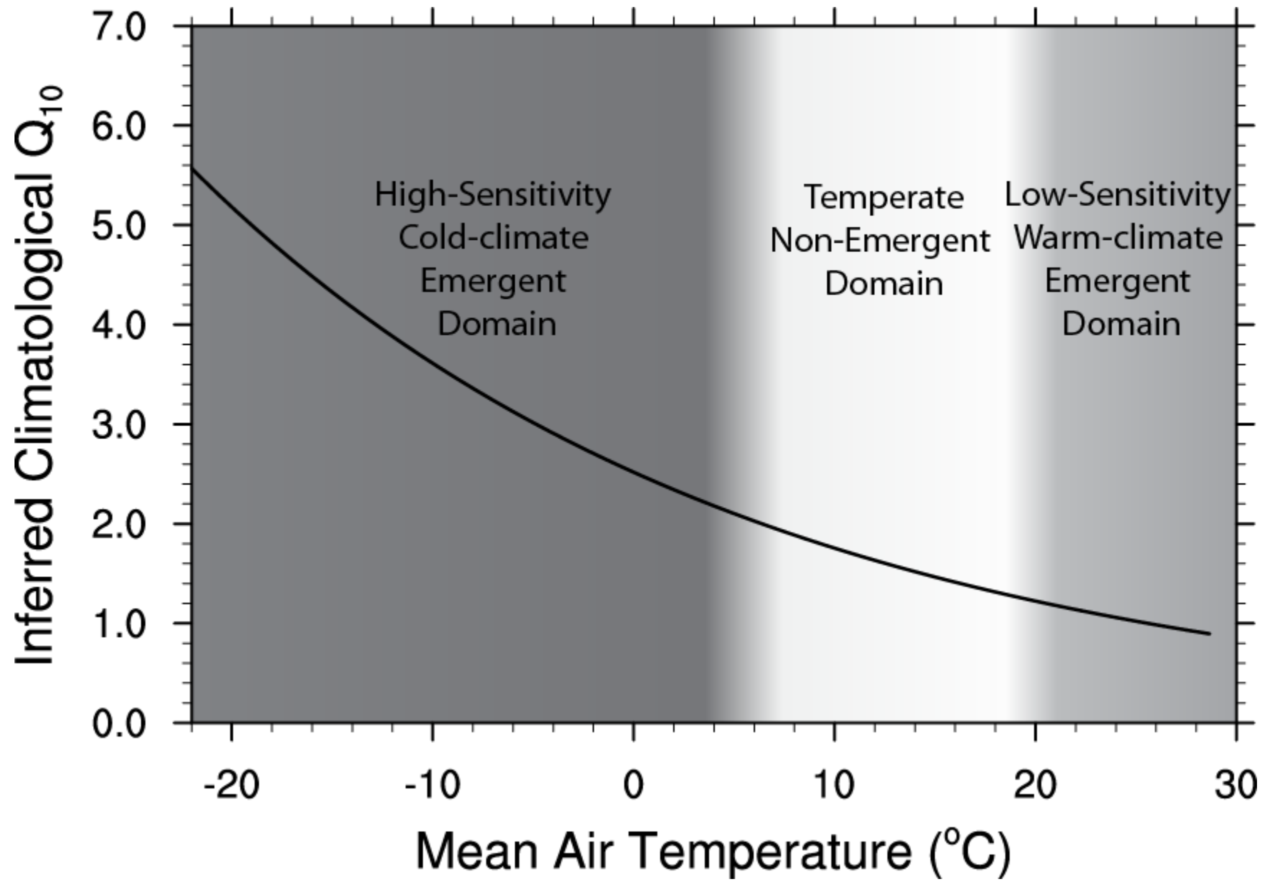




Isolate temperature from moisture effects by removing gridcells that are either too wet or too dry

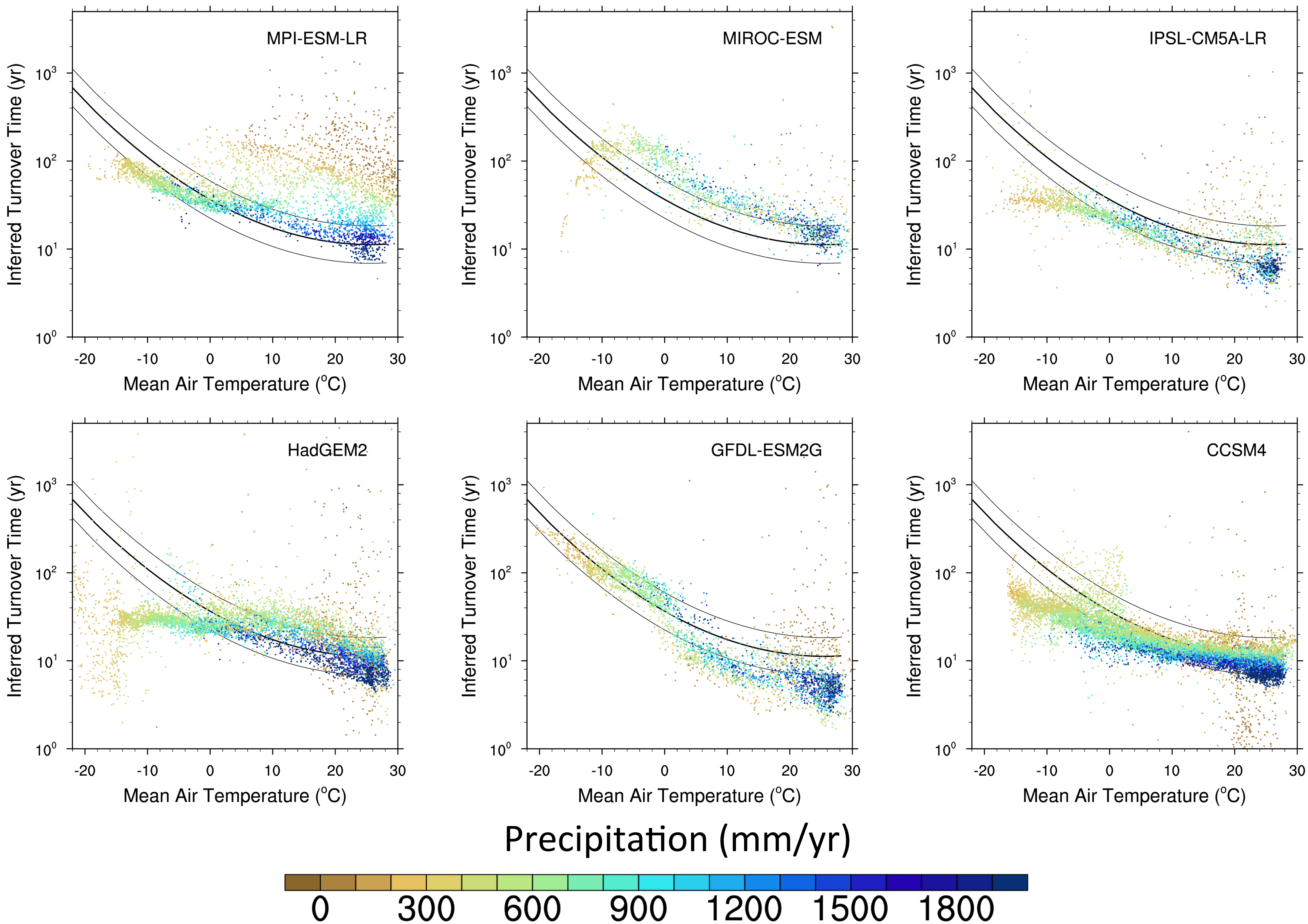


Take derivative of best-fit curve to estimate a "climatological Q_{10}"



Note that this is just for carbon to 1m depth, so different from the larger permafrost carbon issue, which is dominated by deep carbon.

How do CMIP5 ESMs compare?



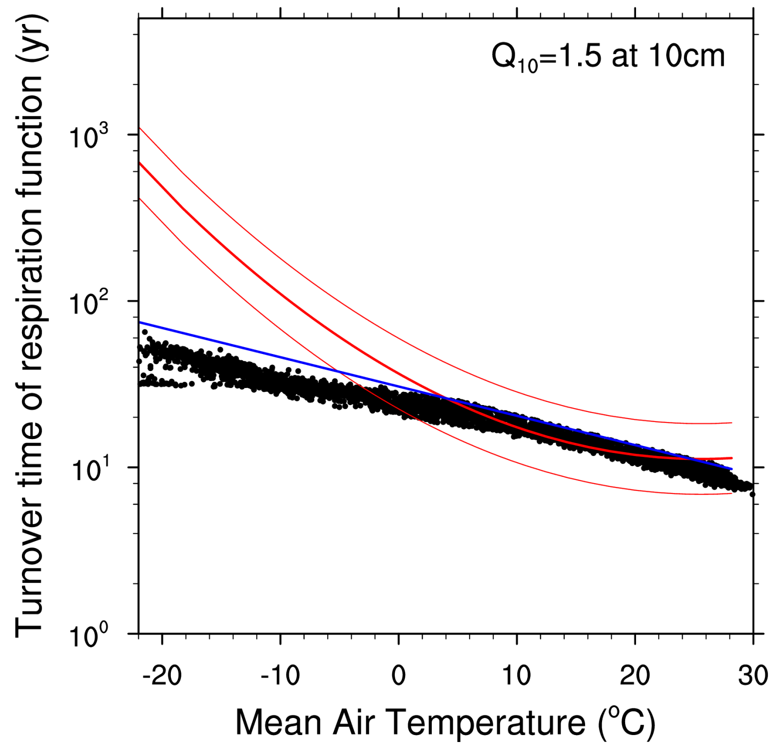
A simple scaling theory for why temperature sensitivity is high in cold climates

Using daily soil temperatures and mean annual air temperatures from a land surface model:

$$k = f(T)$$

$$\tau = 1/\overline{k}$$

Method 1: $Q_{10} = 1.5$, using 10cm soil temperatures



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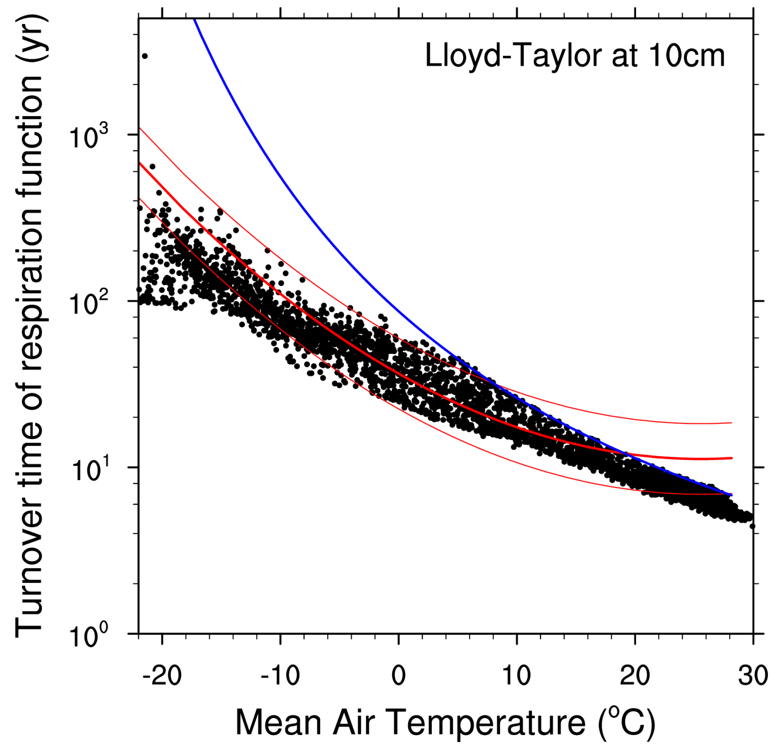
Method 2: Arrhenius equation following Lloyd and Taylor (1994), using 10cm soil temperatures



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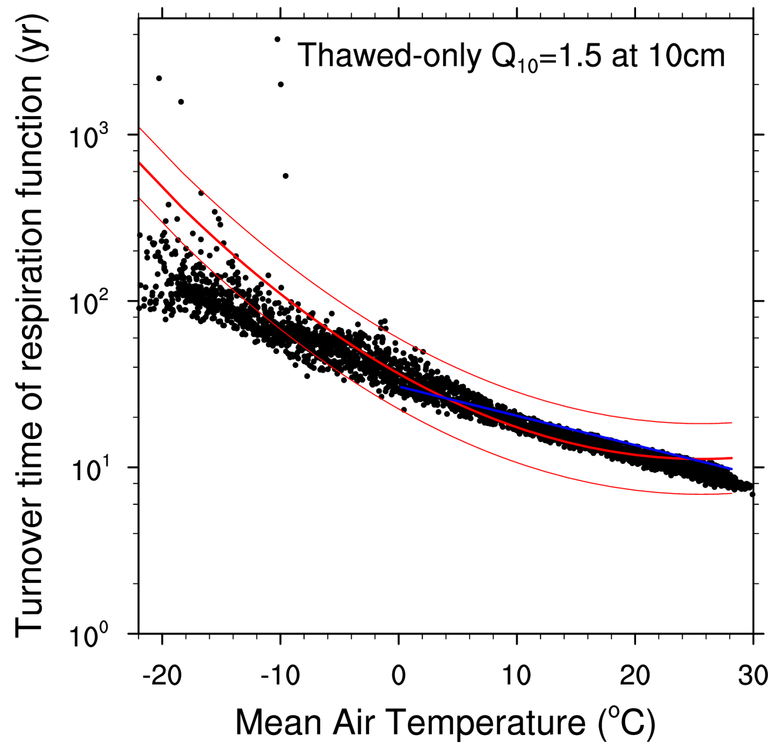
Method 3: Q_{10} = 1.5 when thawed, *k = 0* when frozen, using 10cm soil temperatures



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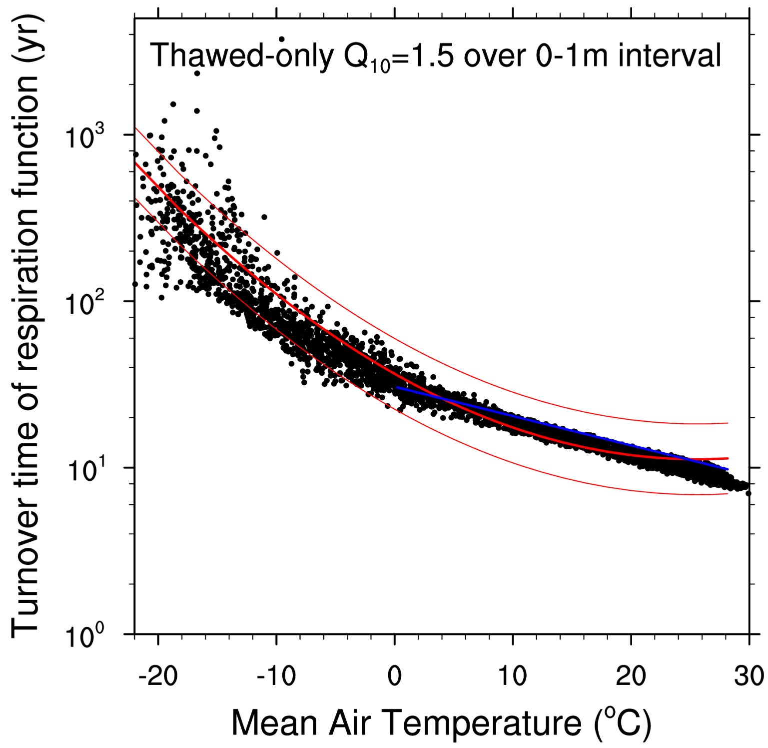
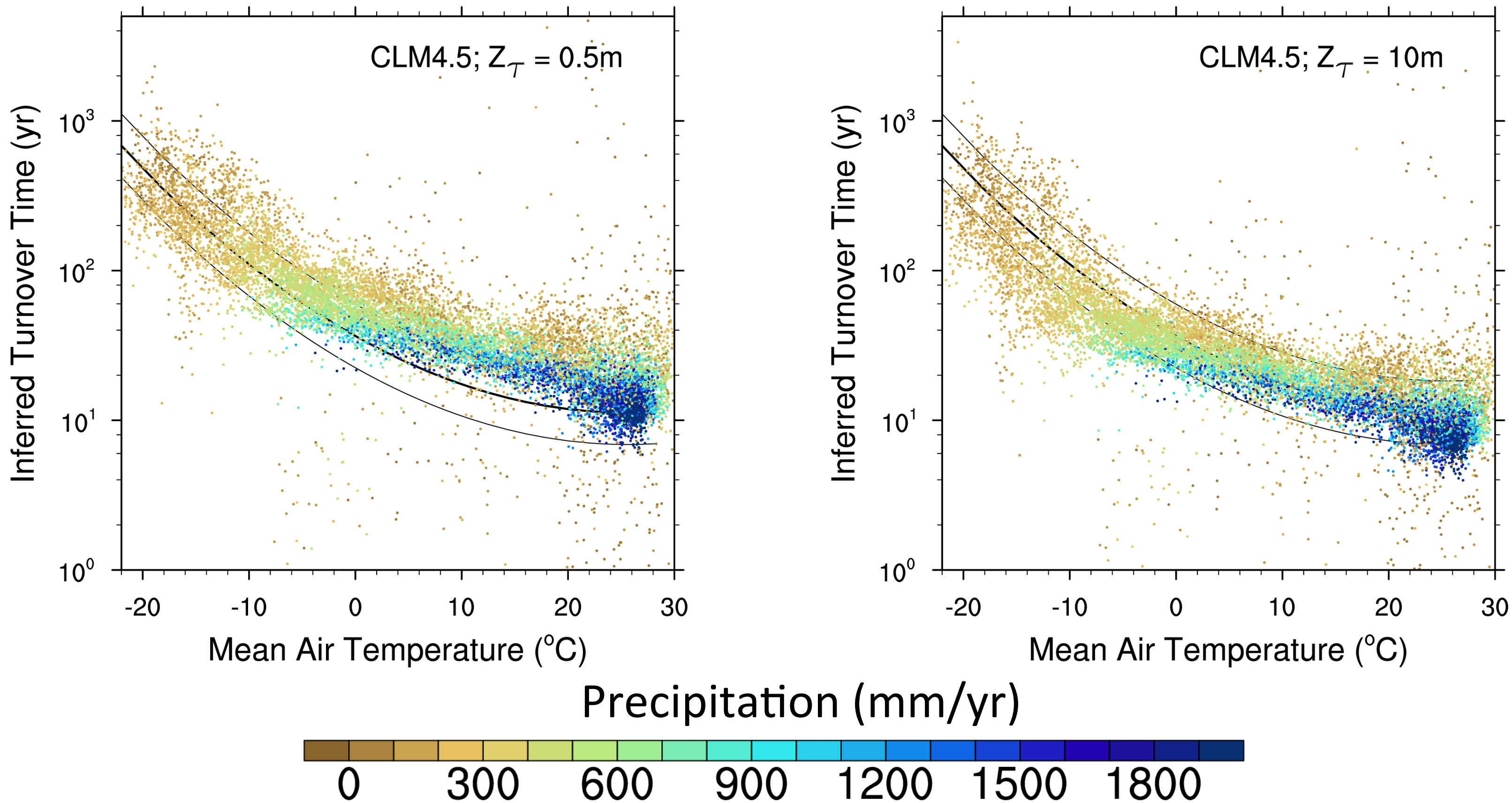


Method 4: Q_{10} = 1.5 when thawed, *k = 0* when frozen, using soil temperatures at each level, and then calculate mean k across 0-1m interval

Implication: Properly representing the scaling of freeze/thaw in both volume and time is essential to understanding temperature controls on soil carbon cycling

How does CLM4.5 compare to observational benchmark?



- CLM4.5 *can* approximate the change in slope due to vertically-resolved soil carbon dynamics
- Comparison against benchmark supports parameter choice that allows decomposition to proceed freely in deep soils

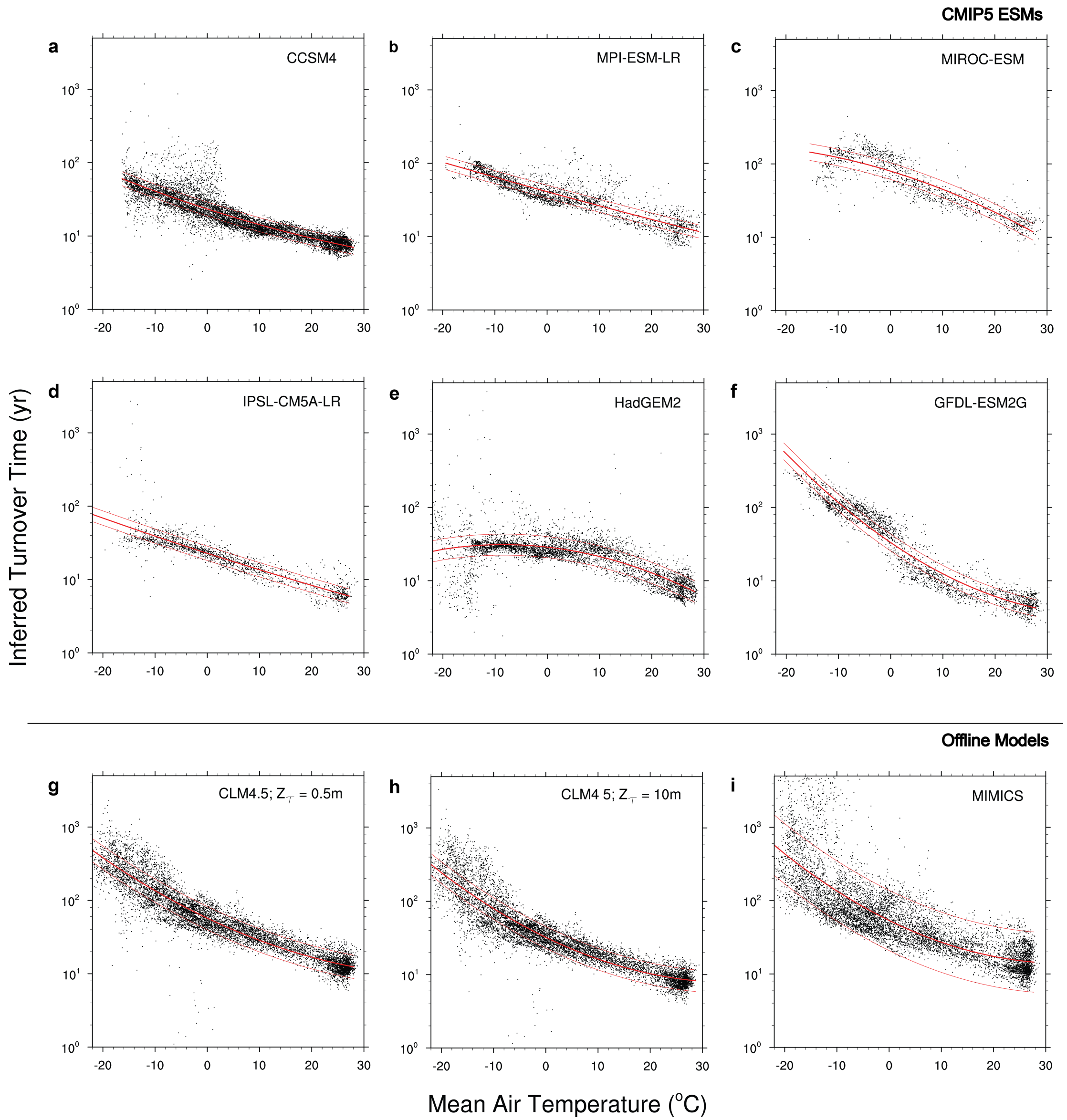
Development of an actual Benchmark

- Approach 1: Filter data as observations (P-PET threshold), fit quadratic to log(tau), and compare regression coefficients
- Approach 2: Filter data, bin by temperature interval and take mean across bins, calculate RMSE difference between that and obs

Benchmarking results

Model	**RMSE relative to observational trend**	**Quadratic Regression Intercept (*c*)**	**Quadratic Regression Linear Coefficient (*b*)**	**Quadratic Regression Coefficient (*a*)**	**Residual Variance after Regression**
Observations	n/a	1.56E+00	-4.01E-02	7.84E-04	9.91E-02
CCSM4	0.26	1.37E+00	-2.28E-02	1.49E-04	1.98E-02
MPI-ESM-LR	0.19	1.61E+00	-1.95E-02	2.86E-05	1.72E-02
GFDL-ESM2G	0.22	1.52E+00	-4.85E-02	5.92E-04	2.88E-02
HadGEM2	0.32	1.46E+00	-8.04E-03	-4.76E-04	4.53E-02
IPSL-CM5A-LR	0.27	1.36E+00	-2.29E-02	5.37E-05	2.08E-02
MIROC-ESM	0.31	1.90E+00	-2.17E-02	-3.17E-04	2.81E-02
CLM4.5, Z_{τ} =0.5m	0.18	1.76E+00	-3.39E-02	3.63E-04	5.55E-02
CLM4.5, Z_{τ} =10m	0.11	1.51E+00	-3.44E-02	4.80E-04	4.77E-02
MIMICS	0.18	1.73E+00	-3.49E-02	5.22E-04	3.70E-01

Example of Quadratic regressions on models



Soil moisture control in CLM

CLM equation:

$$r_w = \frac{log\left(\frac{\psi_{min}}{\psi}\right)}{log\left(\frac{\psi_{min}}{\psi_{max}}\right)}$$

Which is from this paper, but…

	CLM value	Original reference
ψ_{max}	-10 MPa	-0.35 MPa
ψ_{min}	saturation	Field capacity (-0.005 Mpa)

Ecology, 68(5), 1987, pp. 1190–1200

BARLEY STRAW DECOMPOSITION IN THE FIELD: A COMPARISON OF MODELS[1]

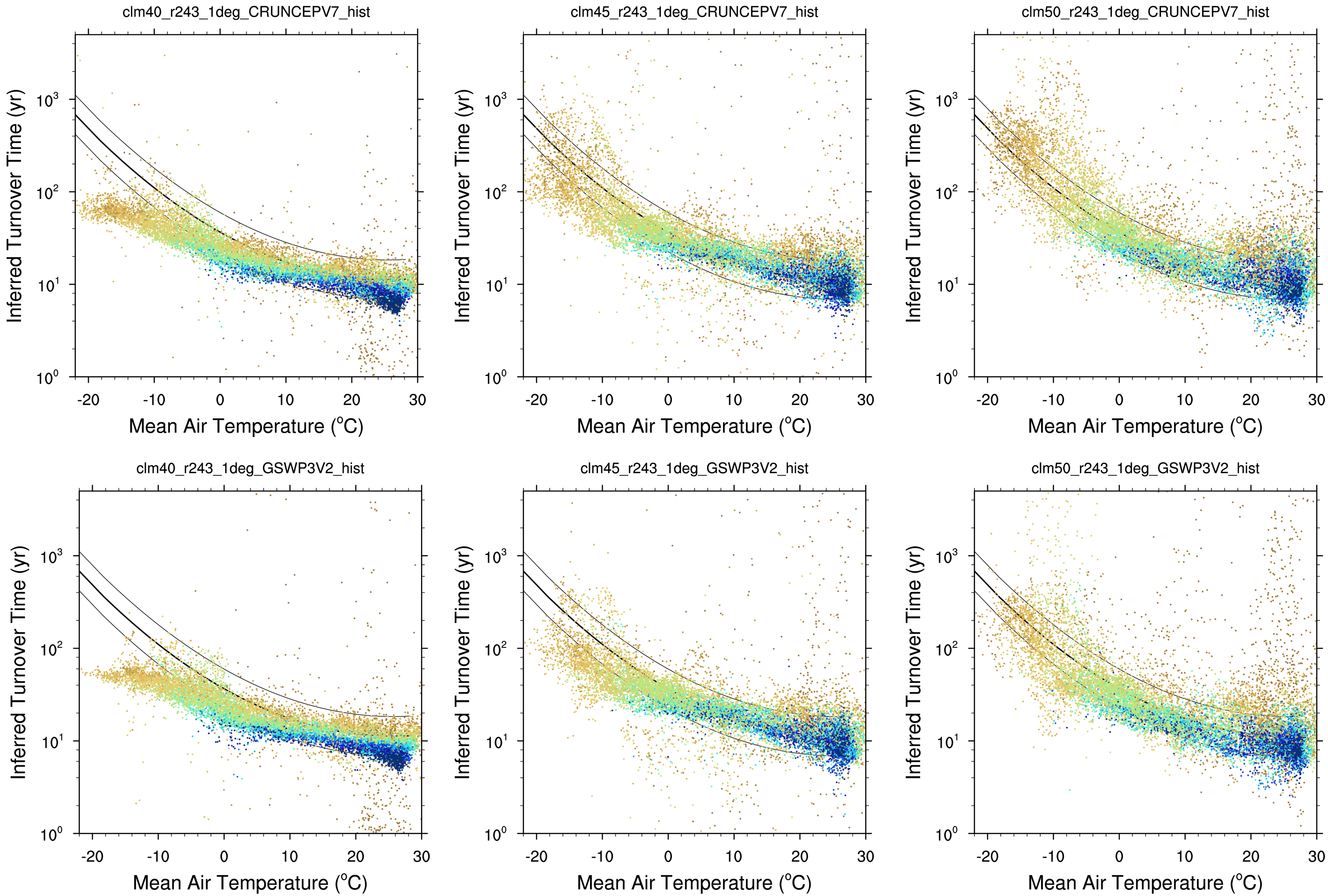
OLOF ANDRÉN AND KEITH PAUSTIAN
Department of Ecology and Environmental Research, Swedish University of Agricultural Sciences, S-750 07 Uppsala, Sweden

Moisture influence was assumed to be a log-linear function of soil water potential (Ψ):

$$E_\Psi = \begin{cases} 1 & ; \Psi > \Psi_{\max E} \\ \dfrac{\log(\Psi_{\min E}/\Psi)}{\log(\Psi_{\min E}/\Psi_{\max E})} & \\ 0 & ; \Psi < \Psi_{\min E} \end{cases} \qquad (6c)$$

where Ψ is the soil water potential and $\Psi_{\max E}$ and $\Psi_{\min E}$ are boundary values for maximum (i.e., wet soil) and minimum (i.e., dry soil) water potentials, expressed in megapascals (as negative values). Since the soil was light in texture and well drained, negative effects on decomposition due to waterlogging were not considered. The response function is similar to others used for soil respiration (Wilson and Griffin 1975, Orchard

Developments along the path: CLM4 -> CLM4.5 -> CLM5

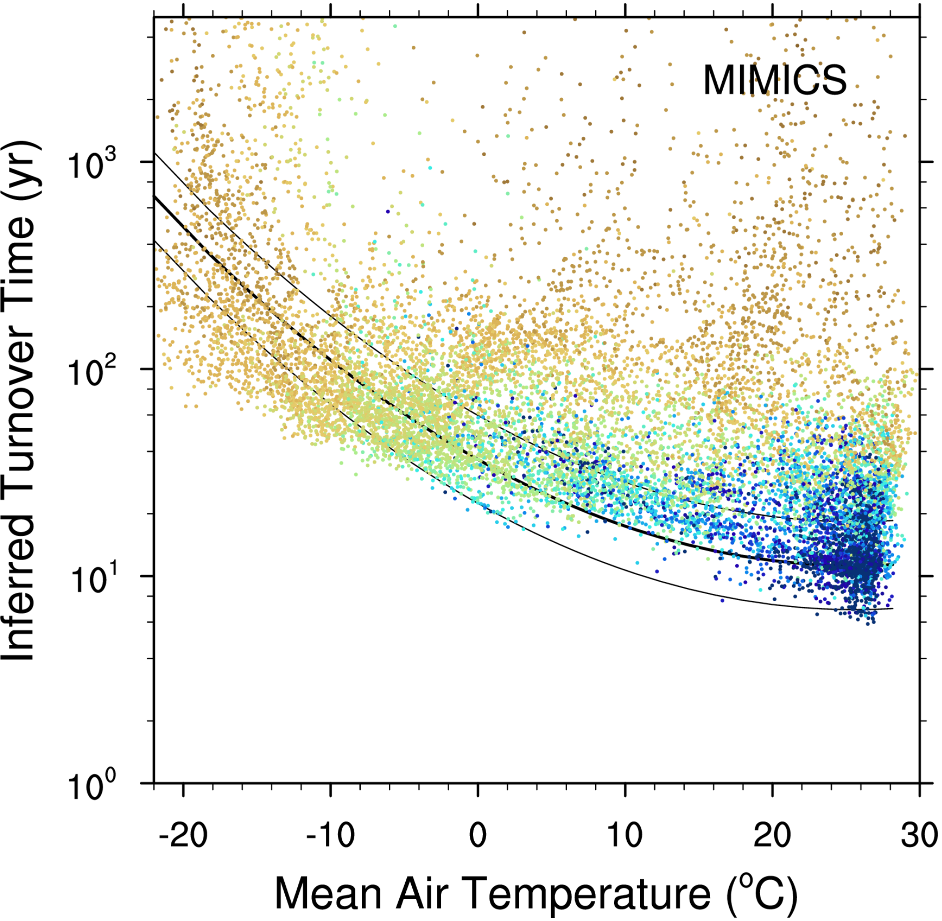


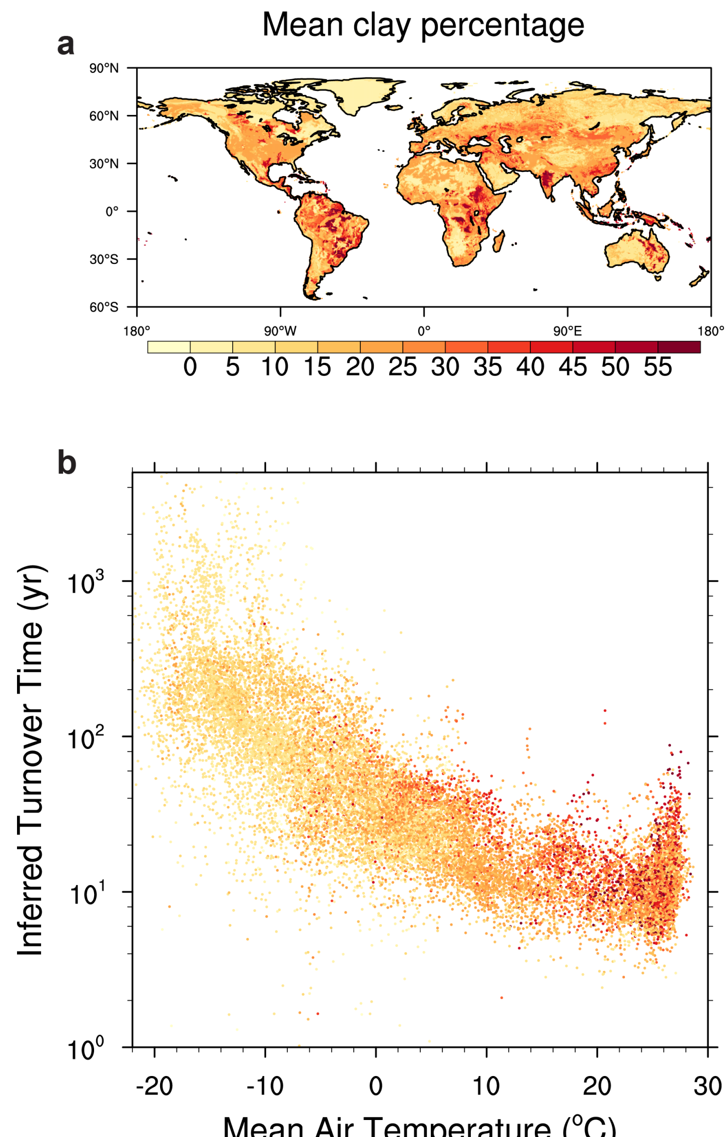
Lawrence et al *in prep*

What's going on with the low climatological Q_{10} in warm climates? Some possible explanations:

- Increased clay content of tropical soils
- Microbial kinetic limitations, either at the community level (Wang et al., 2016) or at the individual level (Tang and Riley, 2015)
- More complex interplay of temperature and moisture effects than our analysis allows
- …

MIMICS and the tropical low-sensitivity regime



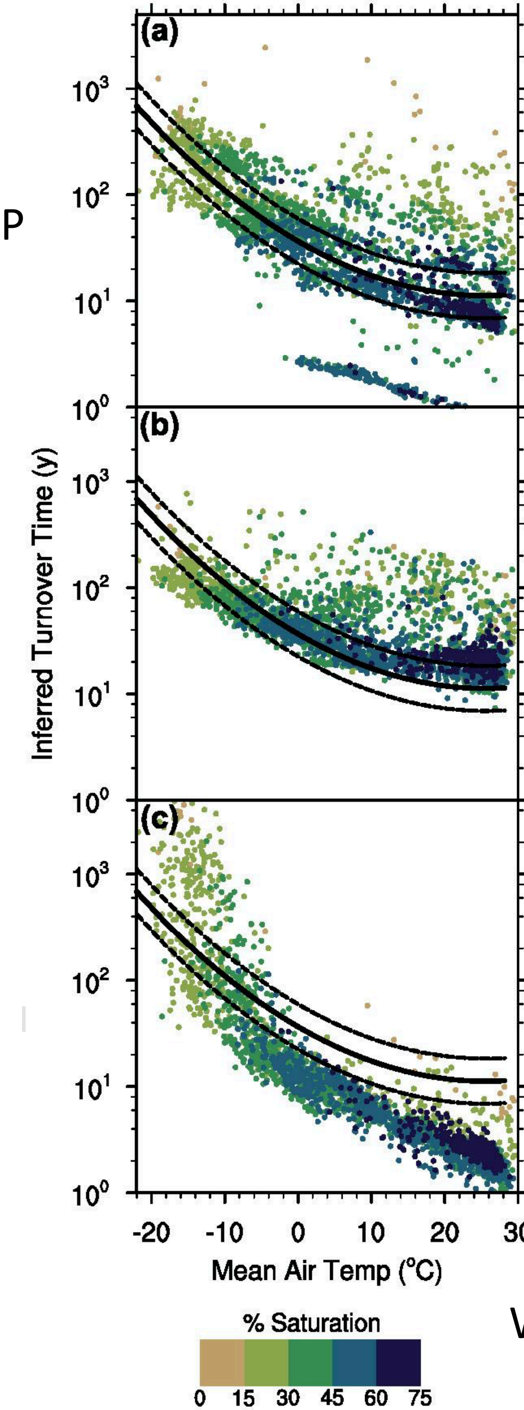


Incorporation of metric in soil Biogeochemical testbed

CASA-CNP

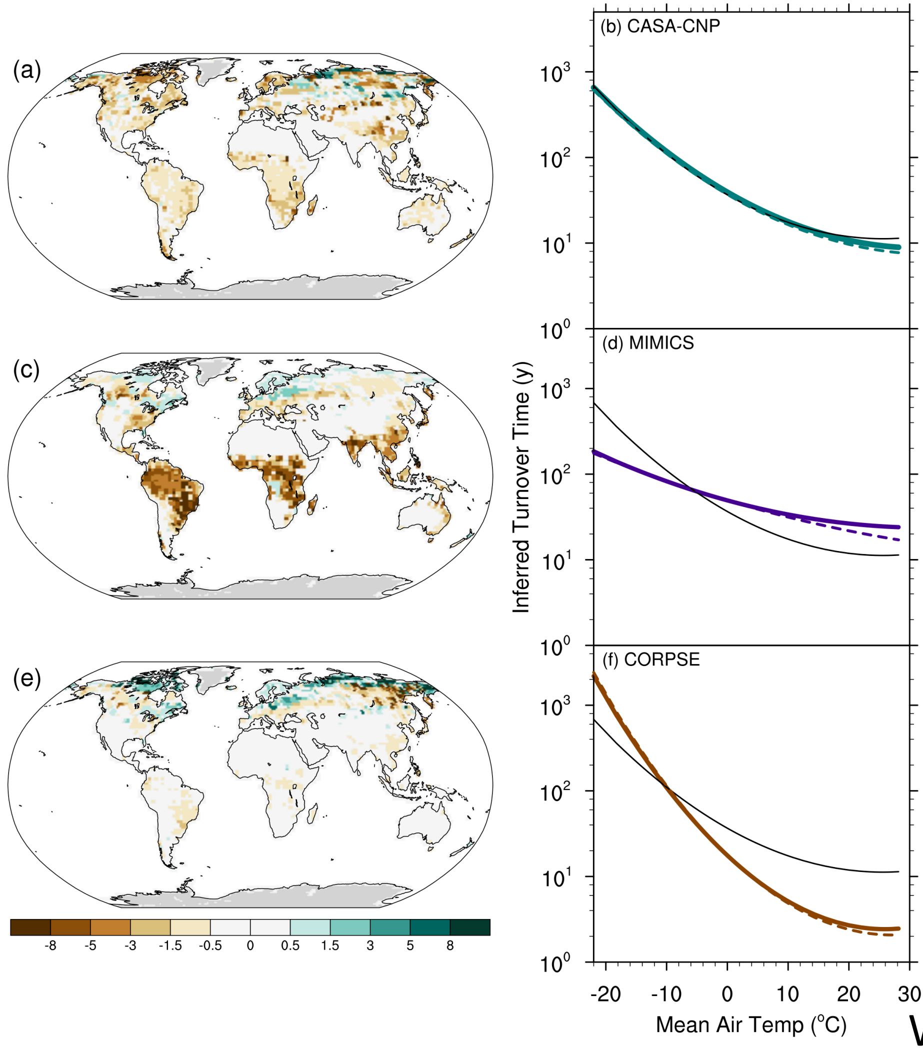
MIMICS

CORPSE



Wieder et al., 2017

“Global Loam” Experiment



Wieder et al., 2017

Conclusions

- We've constructed a global, multivariate relationship that is useful for constraining some of the long-term climate sensitivity of ESM soil models.
- Result is that long-term temperature sensitivity as measured by "climatological Q10" is itself sensitive to temperature, and higher in cold than warm climates
- A simple explanation for high cold-climate sensitivity is a purely physical scaling argument relating soil freeze-thaw dynamics to air temperature
- CMIP5 models don't capture qualitative behavior, which can be captured via quantitative benchmarks, and this systematic bias likely implies that they are underestimating transient soil C sensitivity to warming as well
- Low warm-climate sensitivity remains to be explained; multiple possible reasons, which would have different implications for transient behavior
- Benchmark useful as a constraint in both identifying structural requirements as well as some parameter calibration in CLM